radiation treatment. These curves may be compared to component independent calibration (CIC) estimates of the actual outcome from patients in the cohort. FIG. **16** shows a comparison of observed outcomes and the multivariate model relating the variables (i.e., the calibration) with the estimated dose and BED using the calibration curves. The model accurately predicts treatment outcomes based on dose for a given time. The calibration curves for the multivariable model that includes dose for less than 5% probability of failure and BED demonstrate strong agreement between the estimated and observed 1-, 2-, and 3-year outcomes. Vertical bars represent 95% confidence intervals for observed local failure probabilities.

[0157] The dose with less than 5% probability of failure at a given time may have a wide dose range (e.g., 21.1-277 Gy, BED) based on one example cohort. As compared to the dose used for patients of the cohort, a dose reduction of 23.3% of patients may have provided the desired outcome. The estimated dose from the multivariate model may be safely delivered in a substantial majority (69.8%) of patients.

[0158] In act **1404**, an image is displayed. The image includes the dose information, such as in a report. Any of the approaches to show outcome described for act **44** may be used for display of the dose. The estimated dose may be displayed with the outcome information and/or the time-to-event. For example, the report shows the estimated dose and the estimated local failure probability at a certain point in time. The user may configure the point in time to use. The report may show further information, such as the user (e.g., physician) selecting a dose. This prescribed dose is displayed with an estimate of the local failure probability, allowing comparison for radiation planning.

[0159] FIG. **13** shows a medical imaging system for therapy decision support. The system generates a predication of therapy outcome on a display **130** to support therapy decisions.

[0160] The medical imaging system includes the display **130**, memory **134**, and image processor **132**. The display **130**, image processor **132**, and memory **134** may be part of the medical imager **136**, a computer, server, workstation, or other system for image processing medical images from a scan of a patient. A workstation or computer without the medical imager **136** may be used as the medical imaging system.

[0161] Additional, different, or fewer components may be provided. For example, a computer network is included for remote prediction based on locally captured scan data. As another example, a user input device (e.g., keyboard, buttons, sliders, dials, trackball, mouse, or other device) is provided for user interaction with the outcome prediction.

[0162] The medical imager **136** is a computed tomography, magnetic resonance, ultrasound, positron emission tomography, or single photon emission computed tomography scanner. For example, the medical imager **136** is a computed tomography system having an x-ray source and detector connected to a moveable gantry on opposite sides of a patient bed.

[0163] The medical imager **136** is configured by settings to scan a patient. The medical imager **136** is setup to perform a scan for the given clinical problem, such as a lung scan. The scan results in scan or image data that may be processed to generate an image of the interior of the patient on the display **103**. The scan or image data may represent a three-dimensional distribution of locations (e.g., voxels) in a volume of the patient.

[0164] The image processor **132** is a control processor, general processor, digital signal processor, three-dimensional data processor, graphics processing unit, application specific integrated circuit, field programmable gate array, artificial intelligence processor or accelerator, digital circuit, analog circuit, combinations thereof, or other now known or later developed device for processing medical image data. The image processor **132** is a single device, a plurality of devices, or a network. For more than one device, parallel or sequential division of processing may be used. Different devices making up the image processor **132** may perform different functions. In one embodiment, the image processor **132** is a control processor or other processor of a medical diagnostic imaging system, such as the medical imager **136**. The image processor **132** operates pursuant to stored instructions, hardware, and/or firmware to perform various acts described herein.

[0165] In one embodiment, the image processor **132** is configured to train one or more machine learning networks. Based on a user provided or other source of the network architecture and training data, the image processor **132** learns features for encoders, decoders, discriminators, or other network parts to train the network. A multi-task generator is trained using ground truth and corresponding losses for two or more tasks. One task is outcome prediction. The other task uses data unlabeled for outcome, such as radiomic features, segmentation, non-image data, and/or other information that may be more commonly available than outcome and/or may be derived from the available images.

[0166] Alternatively or additionally, the image processor **132** is configured to apply one or more machine-learned generative networks or generators. For example, the image processor **132** applies scan data from the imager **136** to a machine-learned multi-task network. The network predicts a result of therapy for the patient in response to the input of scan data. The network may include an encoder of an autoencoder trained in an unsupervised manner and a fully-connected network configured to receive an output of the encoder to predict the therapy outcome result. The encoder was trained with a decoder of the autoencoder to estimate an input from the output of the encoder in training in the unsupervised manner.

[0167] The image processor **132**, using the machine-learned network, may predict a time-to-event after therapy for the patient in response to input of scan data. The network may be multi-task as having been trained with a task in addition to the outcome or survival prediction. For example, the training includes loss for segmentation or radiomic or other image features as well as an outcome or survival loss. In application, this extra task may not be used.

[0168] The image processor **132** may be configured to cluster. The output of the encoder of the machine-learned network or other deep learned features are used in clustering to identified similar patients. Patients with similar clustering of values of the deep-learned features, such as bottleneck features, are found using the clustering.

[0169] The image processor **132** is configured to generate an image. An image showing the predicted outcome is generated. The outcome may be displayed with an image of